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Automatic ECG signal denoising and arrhythmia classification using deep learning

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Abstract:

Arrhythmia identification plays an important role in treating cardiovascular diseases. Electrocardiogram is used to study the heartbeats clinically. ECG signals acquired may contain noise in them which misleads the identification of arrhythmia. In this work, an automatic signal denoising method using denoising autoencoders based on long short-term memory named LDAE is proposed to remove the noise from signals. The collected noisy ECG signals and processed clean signals are used to train the denoising model to reconstruct the input signals without noise. Then the reconstructed ECG signals are given as input to deep multilayer perceptron algorithm to identify different types of arrhythmias. Root mean square error and signal to noise ratio are used to evaluate the performance of reconstructed signals. An average SNR and RMSE of 27.5 and 0.037, respectively was achieved. Results indicate that for MLP, accuracy, precision, recall, and F1 score obtained are 98%, 98.57%, 97.25%, and 97.45%, respectively.

Keywords: Arrythmia, denoising, electrocardiogram (ECG), classification, autoencoder, long short-term memory, deep learning

1. Introduction

Numerous cardiovascular diseases (CVDs) are growing, especially after being infected with the COVID-19, becoming the leading cause of death globally, constituting around 32% of all global deaths [1]. As per the world health organization (WHO), 7.5 million people are killed in 2015 due to CVDs, and most of the deaths occurred in underdeveloped counties [1]–[5]. The best way to manage risk factors associated with these CVDs is to monitor the heart rhythms. The vital diagnostic tools used to monitor heart rhythms are tracing the heart's electrical activity known as electrocardiography (ECG) waveform. Tracing a typical ECG signal for each cardiac cycle generally consists of tracing P-wave, a QRS complex, and a T-wave representing atrial depolarization process, ventricular depolarization process, and ventricular repolarization, shown in Fig. 1. The remaining portions of the ECG signal include the ST, PR, and QT intervals. Abnormal cardiac rhythms known as arrhythmias occur due to a strange sequence of heart electrical impulses. These irregular sequences can be observed in ECG change in the waveform sequence [6], [7]. Four general types of arrhythmia are supraventricular tachycardia, extra beats, bradyarrhythmia, and ventricular arrhythmias [8]–[10]. The ECG signals of different cardiac arrhythmia conditions are Arrhythmias may occur in any heart chambers, atriums, and ventricles. This fatal CVD, Arrhythmia, may lead to sudden cardiac arrest, bradycardia, or tachycardia leading to death [1], [5]. Hence frequent monitoring of arrhythmia plays a significant role in CVDs diagnosis and prevention.

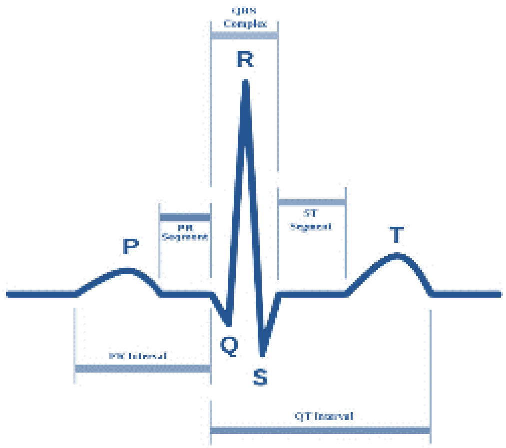


Fig.1: General ECG signal waveform

The classification of arrhythmias based on ECG signals' varying and complex nature amid different subjects is time-consuming and challenging [11]. The rapid advancement of deep learning algorithms and the wide availability of digital ECG data presents improvements in automated ECG classification. The neural network (NN) outperformed various applications and is more widely used in automated ECG classification. Research on automated ECG classification with NNs is presented in [12]–[22]. Various classifying algorithms are proposed and implemented by researchers for the classification of ECG signals with high accuracy support medical professionals. Kiranyaz et al. [12] fused the classification process and feature extraction by implementing 1-D Convolutional neural networks (CNNs). This fusion resulted in better efficiency in both computation and speed, which can be beneficial. By using empirical mode decomposition (EMD) and discrete wavelet transform (DWT) features and radial basis function neural network (NN) classifier, the accuracy of 99.88% was reported by Shaoo S et al. [13] in classifying six types of ECG signals.

F Khalaf et al. [14] proposed an SVM classifier and a CAD system based on principal component analysis (PCA) using statistical features and spectral correlation. An accuracy of 98.61% in spectral correlation classifying five-beat types is obtained. Geometry-based features resulted in improved accuracy. An algorithm with an average accuracy of 95.91% for detecting shockable rhythms using the Support vector machine (SVM) model is presented by M Nguyen et al. [15]. A powerful computerized system using a composite dictionary (CD) is introduced by M Raj et al. [16]. This CD consists of the sine, Stockwell, and cosine analytical functions to efficiently show ECG signals. This approach decomposed the ECG signal into non-stationary and stationary components with a high detection accuracy of 99.23%. A novel three-layer deep genetic ensemble of classifiers (DGEC) is proposed by Pławiak et al. [17] to detect 17 types of ECG arrhythmia using cardiac ECG signals. The proposed model obtained an accuracy of 99.38%. This DGEC model has a complex structure and requires features extraction compared with other deep learning models. Tuncer et al. [18] employed a novel hexadecimal ternary pattern method to detect heart arrhythmia. Seventeen types of ECG arrhythmia are classified using multilevel wavelet feature extraction, and an accuracy of 95% on ECG signal is achieved.

A novel principal component analysis network (PCAN) system with a linear SVM method is proposed for classification by W Yang et al. [19]. The novel classifier system identified heartbeats with an accuracy of 97.78%. M Rai et al. [20] presented a hybrid feature extraction technique using multiresolution DWT and multilayer-probabilistic neural network (PNN) classifier in detecting only right bundle branch block (RBBB) and the left bundle branch block (LBBB) types of arrhythmias. The proposed system showed 99.07% overall accuracy. Using the MIT-BIH arrhythmia database and employing nonlinear morphological features and a voting-based scheme known as ICEEMED, Kandala R et al. [21] presented a method for feature extraction and classification of cardiac ECG signals different classes of cardiac arrhythmia. The proposed model achieved a classification accuracy of 100.00% and 90.40% on unknown and fusion classes. However, the performance of a few heartbeats like an aberrated atrial, atrial premature contraction, junctional premature beats class, and supraventricular is still low compared to the other classes where the improvements are to be done. A novel deep genetic ensemble of classifiers (DGEC) with a three-layer is designed by Pławiak et al. [22] to detect heart arrhythmia using ECG signals. The developed model obtained an accuracy of 99.38% with classification in detecting seventeen types of ECG arrhythmia. The disadvantages of this DGEC model are its complex structure and require features extraction compared to the other deep learning models.

Most of the studies from the existing literature needs prior domain knowledge and are mathematically extensive. Such methods depend on the parametric inputs given by the user and are prone to errors. A well-developed automatic noise reduction method can overcome these limitations. Thus, the novelty of the work is to develop an automatic signal denoising method using denoising autoencoders (DAE) based on long short-term memory (LSTM) named LDAE to remove the noise from the ECG signals. First, the collected noisy ECG signals and processed clean signals are used to train the denoising model. Upon training, the proposed denoising model will be able to reconstruct the input signals without noise. Then the reconstructed ECG signals are given as input to the deep learning classification algorithm to identify different types of arrhythmia. Finally, the denoising and classification performances are reported.

2. Data acquisition and methodology

In this work, a methodology is proposed to denoise the noisy ECG signals and classify the normal and arrhythmic ECG signals. The ECG signals are acquired from different age groups using 12-leads. A public data set from Chapman university and Shaoxing hospital [23] is used in this work. The ECG recording are obtained from 10,646 subjects, of which 55.95% males, from 4 to 98 age groups. The ECGs are recorded for 10 seconds at 500 Hz sampling rate using 12-leads with 32-bit resolution over a 4.88 mV range. Each ECG signal consists of 5000 samples. The acquired 12-dimension ECGs features 11 cardiovascular rhythms. Two licenced physicians independently annotate the datasets to make them more reliable for data driven studies. The 11 cardiovascular rhythms in the dataset are: atrial fibrillation (AFN), atrial flutter (AFT), atrial tachycardia (ATA), atrioventricular reentrant tachycardia (ART), atrioventricular node reentrant tachycardia (ANRT), sinus bradycardia (SBA), sinus irregularity (SIY), sinus rhythm (SRM), Sinus Tachycardia (STA), supraventricular tachycardia (ST), and sinus atrium to atrial wandering rhythm (SAAW). Since the dataset contains rare rhythms with less data [23], the 11 rhythms are merged into 4 groups according to the guidelines [24]–[26]. Table 1 gives the details of the merged groups. Butterworth low pass filter are used in this dataset to obtain clean ECG signals.

Table 1. Details of merged data.

S. No.	Merged to	Merged from
1	AF	AFT, AFN
2	SB	SBA
3	SR	SRM, SIY
4	SVT	STA, ST, ATA, ART, ANRT, SAAW

A signal denoising method using denoising autoencoders (DAE) is proposed to remove the noise from the ECG signals. First, the collected noisy ECG signals and processed clean signals are used to train the denoising model. Upon training, the proposed denoising model will be able to reconstruct the input signals without noise. The reconstructed ECG signals are given as input to the deep learning classification algorithm to identify different types of arrhythmia. Fig. 2 represents the proposed methodology. The detailed process of signal denoising is explained in the next section.

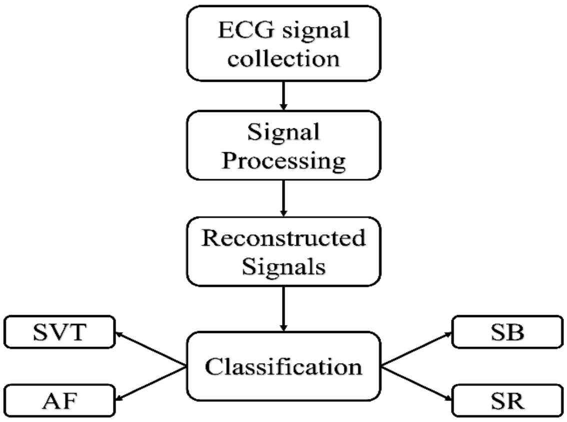


Fig. 2. Proposed methodology block diagram

3. Signal denoising

The ECG signals acquired may contain noise due to noise sources like muscle contraction, electrode contact noise, baseline wandering, power interference, motion artifacts, and random noise. Noise in the signals lead to misclassification due to presence of unwanted peaks in the signals. In this work, a signal denoising method using denoising autoencoder based on long short-term memory (LSTM) named LDAE is proposed. LDAE takes the corrupt signal as input and gives denoised signals as output. During training, both clean ECG signals and corrupted ECG signals are given as input to the LDAE. The clean ECG signals are generated using Butterwoth filtering with local polynomial regression smoother and non-local means, detailed by Zheng et al. [23]. An autoencoder is an unsupervised artificial neural network model that consists of input layer, encoder, and decoder layers. ECG signals are given as input to the input layer. The encoder codes the inputs and at the same time the decoder learns the features from the encoded inputs and further reconstructs the given original input. Fig. 3. gives the structure of LDAE proposed in this work.

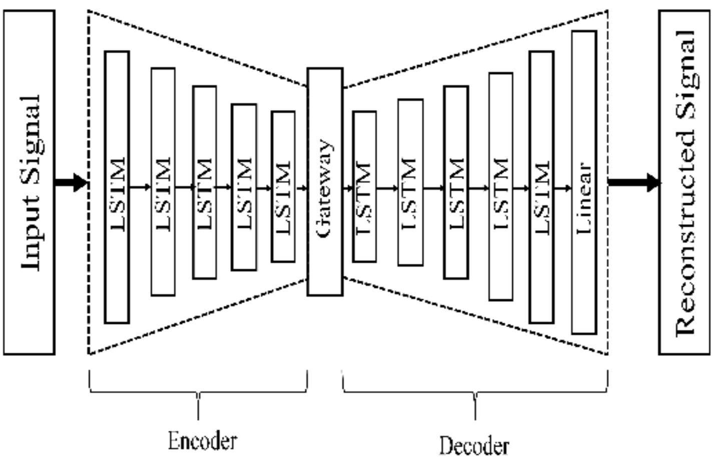


Fig. 3. Structure of LDAE

LDAE proposed in this work effectively learns the ECG time series characteristics and denoises the signals. LDAE consists of input layer, encoder, and decoder layers as shown in Fig. 3. The encoder consists of five layers of LSTM networks. The first LSTM layer is the input ECG signal transformation tensor with 1024 as the dimension of the hidden layer. The dimension of second LSTM layer was set to 512 and it is the transformation tensor of first LSTM layer output. Output from the second layer is given as input to the third LSTM layer and third layers' output is given as input to the fourth LSTM layer. Each LSTM layer is a transformation tensor of output from its pervious layer and this process continuous till the fifth LSTM layer in the encoder. The dimensions of the third, fourth, and fifth LSTM layers are set to 256, 128, and 64, respectively. An activation function is defined at each stage to sequentially process the input ECG signals. The hidden layers reduce the dimension of the input ECG signal data by compressing it and by extracting hidden time-series features through LSTM network. The compressed data from the fifth LSTM layer of the encoder is passed through gateway and is given as input to the decoder.

Table 2. Details of each layer of LDAE.

Layer no.	Layer name	Activation function	Output size
Encoder			
1	LSTM	Tanh	1024
2	LSTM	Tanh	512
3	LSTM	Tanh	256
4	LSTM	Tanh	128
5	LSTM	Tanh	64
Decoder			
6	LSTM	Tanh	64
7	LSTM	Tanh	128
8	LSTM	Tanh	256
9	LSTM	Tanh	512
10	LSTM	Tanh	1024
11	Linear	Tanh	1024*5000

The decoder part of LDAE contains six layers with five LSTM layers and a linear layer that are connected step-by-step with each other. The five LSTM layers in the decoder are the transformation tensors of their pervious layers and the sixth layer is a conversion tensor of the output from the fifth LSTM layer. The encoded data is decompressed in the decoder using LSTM layers and the linear layer transforms the output from the fifth LSTM layer into standard ECG signal data. The details of the different layers in the LDAE are given in Table 2. As ECG signal consists of times-series data, a single group of ECG data sequence with size of 1*5000 was given as input to the LDAE. The LSTM layers, 1-5, compresses the input data from 1*5000 to 1*64 and extracts and learns time series features from the data. Reconstruction of the compressed data to original size of 1*5000 is done using layers 6-11. The output of the LDAE is a denoised signal of the input ECG signal. The model parameters are updated using back-propagation to reduce the error between input data and expanded data.

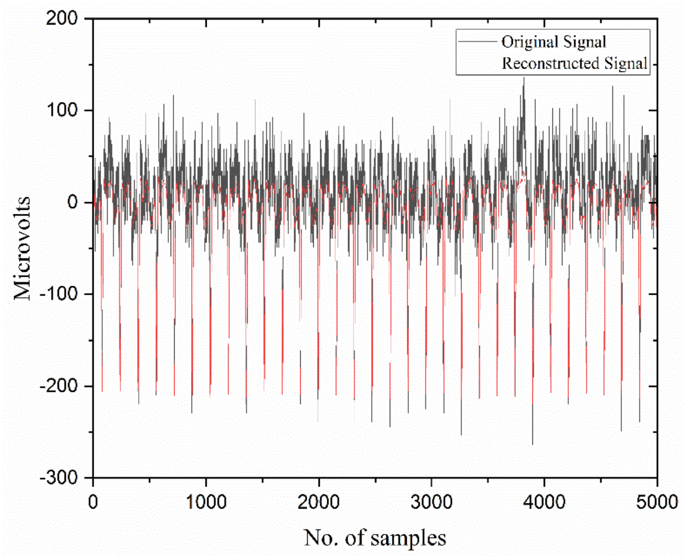


Fig. 4. Reconstructed signal for ECG with high and low frequency noise record no. 100

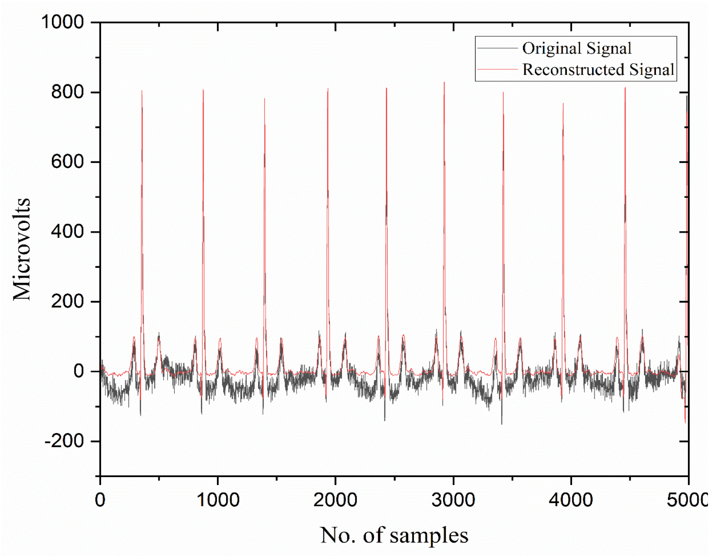


Fig. 5. Reconstructed signal for ECG with baseline wandering record no. 2000

The denoising is performed on 10,646 ECG records using LDAE to get the reconstructed noise-free signals. As a representation, the reconstructed signals for the ECG record no. 100 and 2000 are shown in Fig. 4 and Fig. 5, respectively. ECG record no. 100 consists of both low and high frequency noise which is processed using LDAE to get the denoised signal, Fig. 4. Baseline wandering is the source of noise for ECG record no. 2000. The denoising performance of the proposed LDAE is evaluated using widely used performance metrics, root mean square error (RMSE) and signal to noise ratio (SNR) [27]–[29]. The RMSE gives the variance between the model output and the actual output, given by Eq. 1. A smaller value of RMSE represents better performance of the model. The amount of noise energy in the signal introduced due to compression and decompression of the signal is given by SNR, Eq. 2, and is measured in decibels (dB). SNR greater than 1 represents more signal than noise. A higher value of SNR represents good signal quality.

$$RMSE = \sqrt{\frac{1}{Z}\sum_{n=1}^{Z-1}[y_i - y_i^r]^2} \quad (1)$$

$$SNR = 10\log\left(\frac{\sum_{y=1}^{m}(y_i-\bar{y})^2}{\sum_{y=1}^{m}(y_i-y_i^r)^2}\right) \quad (2)$$

where y_i and y_i^r represents the original signal and reconstructed signal respectively, and $\bar{y}$ gives the mean value of the original signal. The SNR and RMSE values for different ECG record numbers are given in Table 3. Later, these denoised signals are used to classify the heartbeat conditions using deep learning algorithm that is discussed in the next section.

Table 3. Denoising performance of LDAE.

ECG record no.	RMSE	SNR (dB)
100	0.023	27.67
1000	0.036	22.31
2000	0.021	27.73
3000	0.029	26.54
6000	0.052	20.89
8000	0.047	21.07
10000	0.033	23.27

4. Classification and result analysis

The reconstructed signals by LDAE through processing the raw ECG signals are used to classify the types of arrhythmia using a deep multilayer perceptron (MLP). MLP is an unsupervised deep learning algorithm and is a feed forward type of artificial neural networks (ANN). It has interconnected neurons that transfers information among each other. MLP consists of an input layer, hidden layers, and output layer. Fig. 6 shows the architecture of the MLP used in this work. MLP proposed in this work consists of four hidden layers. Each hidden layer has a fully connected layer with 100 nodes. Batch normalization is introduced in the first hidden layer of the MLP. Rectified linear activation unit (ReLu) is used as the activation function in each of the hidden layer. Hyperparameter tuning is the selection of optimal hyperparameters whose value controls the learning process. It minimizes a predefined loss function to give better results. The wrapper is used to connect the scikit learn python library to Keras for hyperparameters tuning, and GridSearchCV (10-fold cross-validation) is used to find different hyperparameters. Dropout is a regularization technique of MLP to avoid overfitting, thus generalizing the model. Model is likely to result in better performance when dropout is used on a larger network, allowing the model to learn independently. Table 4 gives the values of the hyperparameters.

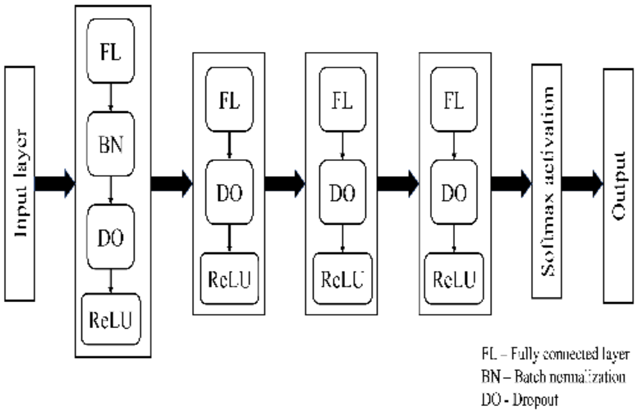
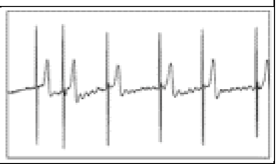
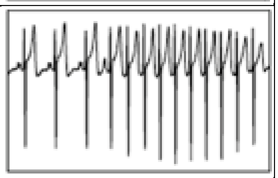
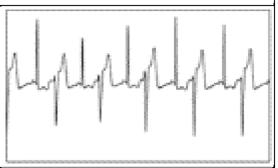
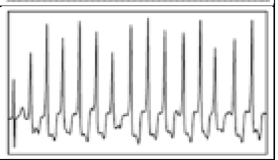


Fig. 6. MLP architecture used in arrhythmia classification

Table 4. MLP hyperparameters.

Hyperparameter	MLP
Batch size	128
Dropout	0.2, 0.2, 0.2, 0.2
Learning rate	0.001
No. of epochs	300
Hidden layers	4
Optimization algorithm	Adamax
Neuron activation function	ReLU
No. of neurons	100, 100, 100, 100

Table 5. Arrythmia dataset.

Class name	Training data (80%)	Testing data (20%)	Total	Sample ECG
AF	3111	778	3889	
SB	1780	455	2225	
SR	1780	455	2225	
SVT	1846	461	2307	

Arrhythmia classification is performed using the reconstructed signals obtained from the previous section using MLP algorithm. The classification algorithm is trained using 80% data, and the remaining 20% is used as test data. Training data (80%) is further divided into training and validation datasets, and the remaining 20% data is test data used to evaluate the performance of the trained model. The details of the dataset are given in Table 5. In the training process, k-fold cross-validation is used, so that model is trained on different subsets of train data, resulting in a more generalized model further minimizing the chances of overfitting. In the present study, 10-fold cross-validation is used on the data sets. In the MLP model, four hidden layers are present in between the input and output layers. Before training the model, GridSearchCV is used to find the optimum hyperparameters on the training data set. During training, the model is evaluated on a validation dataset after each epoch. If the performance of the model on the validation dataset starts to degrade (e.g., loss begins to increase or accuracy begins to decrease), then the training process is terminated at that point. Accuracy, precision, recall, and F1 score are used to evaluate the classification performance. The higher the values of these metrics, the higher will be the fault classification performance. For MLP, accuracy, precision, recall, and F1 score obtained are 98%, 98.57%, 97.25%, and 97.45%, respectively. Confusion matrix for the MLP that shows the classification accuracy among different classes is shown in Table 6.

Table 6. Confusion matrix for MLP.

	AF	SB	SR	SVT
AF	10433	213	426	746
SB	107	10008	532	638
SR	0	105	9156	532
SVT	106	320	532	8730

5. Conclusion

Arrhythmia identification plays an important role in treating CVDs. ECG signals acquired may contain noise in them which misleads the identification of arrhythmia. In this work, an automatic signal denoising method using denoising autoencoders (DAE) based on long short-term memory (LSTM) named LDAE is proposed to remove the noise from the ECG signals. First, the collected noisy ECG signals and processed clean signals are used to train the denoising model. Upon training, the proposed denoising model will be able to reconstruct the input signals without noise. Then the reconstructed ECG signals are given as input to deep multilayer perceptron (MLP) algorithm to identify different types of arrhythmia. Root mean square error (RMSE) and signal to noise ratio (SNR) are used to evaluate the performance of the reconstructed signals. Reconstructed signals showed an average SNR and RMSE of 27.5 and 0.037, respectively. Results indicate that for MLP, accuracy, precision, recall, and F1 score obtained are 98%, 98.57%, 97.25%, and 97.45%, respectively.

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